Hierarchical Motion Artefact Compensation in Smart Garments

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Abstract
This work addresses an emerging topic of smart garments, namely how to decouple the application development from the underlying sensing hardware. The idea of a dedicated operating system, introduced in previous work, is further elaborated by proposing a Garment OS architecture. In order to hide hardware-specific issues from the application developer, the Garment OS has to provide with a certain functionality. For example, sensor signals in garments are often affected by different types of artefacts, such as motion artefact or sensor displacement. Therefore, an important functionality of the Garment OS is to reduce the effects of said artefacts. As part of the Garment OS architecture, this paper proposes a hierarchical approach for artefact compensation in smart garments. This method is applied for motion artefact reduction, demonstrated on an example of activity recognition with a capacitive neckband. Results show a promising improvement of recognition accuracy compared to a baseline without artefact detection and compensation.

Author Keywords
Smart garment, artefact compensation, motion artefact, activity recognition, wearable computing

ACM Classification Keywords
I.2.m [Artificial Intelligence]: Miscellaneous.

Introduction

The European funded project SimpleSkin[1] follows the goal of creating "wearable sensing as an app". The project proposes to view smart garments as a layered system, thus to separate the production of the sensing fabric, garment, processing platform, and the development of applications [2]. The goal thereby is to move smart (sensing) clothing from specific, expensive prototype-like systems to widely deployed, mainstream products that support different applications. A key layer of this concept is a dedicated operating system (Garment OS). The Garment OS provides an abstraction, isolating the application developer from the specifics of the underlying sensing hardware. This abstraction allows the development of applications that are independent of a specific garment.

The introduction of a dedicated operating system for smart garments poses some challenges. For example, different sensing capabilities are typically available in garment-based systems. In order to retrieve a specific information, the most adequate sensor has to be selected. Another challenge is to deal with diverse artefacts (*e.g.* motion artefact, sensor displacement), which often affect sensor data in garments. The Garment OS should hide these issues from the application developer. This paper describes an architecture providing the means to address the above challenges. Moreover, as part of the proposed Garment OS architecture, a hierarchical approach for motion artefact compensation is presented. Overall, the paper provides the following contributions:

1. A Garment OS architecture is proposed, with the goal to enable the decoupling of application development for smart garments from the underlying hardware.
2. A strategy to reduce motion artefacts in smart garments is proposed, as part of the Garment OS. This strategy is demonstrated on the example of activity recognition with a capacitive neckband.

[1] http://simpleskin.org/

Related Work

Existing work on smart garment systems typically follows the scheme of continuously reading out measurements from dedicated sensors and extracting information for a specific task. Data processing is usually performed on a central, on-body or remote computing device. A few approaches exist where information extraction is performed on the sensor level, *e.g.* in Curone et al. [3]. Moreover, Harms et al. [5] present a hierarchical data processing concept, where each layer is realised in a different component of a hierarchical hardware architecture. However, none of the existing architectures is designed in a way that application development can be carried out independently from the sensing hardware.

Motion artefact reduction is an important topic in wearable sensing, especially for physiological signals [7]. A plethora of work investigates classical filtering approaches. The challenge is to reduce artefact contamination, while preserving the desired information in the sensor signal. For example, De Luca et al. [4] use Butterworth filtering to reduce the effects of movement artefact and noise in surface EMG signal. However, the spectrum of motion artefacts often overlap with that of the desired signal, thus classical filtering approaches are often inefficient. An alternative approach is adaptive filtering, which involves an additional information source as artefact reference. For example, Wood et al. [8] use an accelerometer attached to a photoplethysmograph (PPG) sensor to perform adaptive filtering of the distorted PPG output.

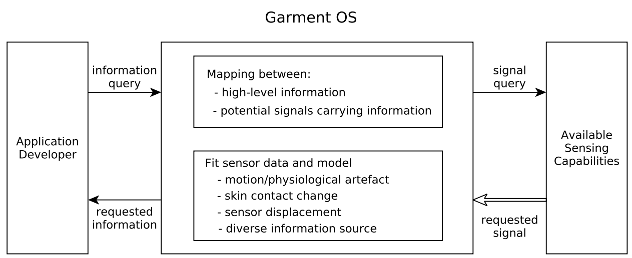

Figure 1: Proposed Garment OS architecture

Garment OS Architecture

This section proposes an architecture for the Garment OS and describes its envisioned functionality. In order to allow an application developer high-level access to the sensing hardware, the Garment OS should provide an interface between the programmer and the available sensing capabilities, as depicted in Figure 1. The envisioned process of accessing the sensing hardware includes the following steps:

1. Developer: information query from Garment OS
2. Garment OS: select the most adequate sensor
3. Garment OS: signal query from sensing hardware
4. Sensing hardware: provide requested signal(s) to Garment OS
5. Garment OS: extract requested information from signal(s)
6. Garment OS: provide requested information to developer

In the context of smart garments, high-level information can be *e.g.* heart rate, skin temperature, or posture of a limb. Examples of available sensing capabilities include inertial sensors, active capacitive sensors [1], or resistive textile pressure sensor matrices [9]. A component integrated into the Garment OS selects the most adequate sensor. This is based on relevance and dynamic availability of sensing capabilities, and considers estimated resource requirements (such as bandwidth or power consumption). For example, heart rate information could be derived from capacitive electrodes placed on chest or wrist, the latter placement being more relevant [1].

Another component integrated into the Garment OS is responsible to extract the high-level information from provided sensor signal(s). For example, in case multi-channel sensor data is provided, this component selects the best information source. Moreover, this component is responsible to compensate diverse artefacts, which often affect smart garments when used in real-life deployments. Potential artefact sources are motion (*e.g.* heart rate while running), physiological signals (*e.g.* breathing overlapping with heart rate signal), skin contact changes (*e.g.* loosened electrode attachment), or garment displacement. The next section proposes a concept to deal with motion artefacts in smart garments.

Motion Artefact Compensation: A Hierarchical Approach

As stated above, classical filtering approaches are often inefficient when dealing with motion artefacts. Considering adaptive filtering, using an additional sensor as artefact reference is often unfeasible in garments, *e.g.* placing an accelerometer in a neckband. Therefore, an alternative approach is required for reducing motion artefacts in smart garments. This work proposes a hierarchical concept, as shown in Figure 2. First the type of artefact (current state) is detected, which is then used in the information extraction step. This concept is suitable for different artefact sources affecting smart garments, *e.g.* heart rate as physiological artefact, a certain way of garment displacement, or a certain degree of loosening of the garment. However, in this work only the compensation of motion artefacts is investigated. Applying the proposed concept to other types of artefacts and its scalability towards multiple (potentially even overlapping) artefact sources remains for future work.

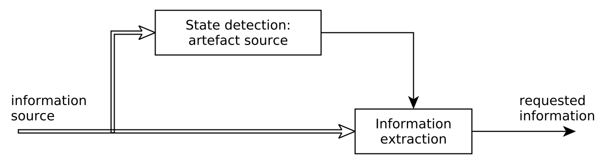

Figure 2: Concept of hierarchical artefact compensation

The proposed approach can be understood as adaptive signal modelling as well: Different strategies are applied on the signal data depending on the system's identified state. Considering only the effects of motion artefacts, two identified states are possible: motion artefact present or not present. This is demonstrated on a concrete, practical use case: motion artefact compensation in activity recognition with a capacitive neckband.

Example: Motion Artefact Compensation in Activity Recognition

The here demonstrated example uses the dataset collected by Cheng et al. [1]. Data was recorded from four subjects, wearing a neckband including capacitive electrodes. Subjects wore the capacitive neckband during computer work (sitting) and walking. In both scenarios they performed a set of activities: nodding, shaking head, looking down/up/left/right/straight, swallowing water, chewing bread, swallowing bread, speaking, and breathing deep. Out of these 12 activities, four (nod, look up, chew bread, swallow bread) were not carried out in the walking scenario for safety reasons. The goal of Cheng et al. [1] was to distinguish all 12 activities, based on the active capacitive sensing principle (movement of muscles, tendons, blood vessels and other tissue inside the neck cause changes, measurable with the capacitive electrodes). An accuracy of 69% was achieved when including data from both scenarios, while reaching 77% when only considering data from the sitting scenario. These results clearly indicate the challenge introduced by motion artefacts. For a detailed description of the sensing principle, the dataset, and the analysis methods and results the reader is referred to Cheng et al. [1].

Methods

The dataset includes data from two states from the artefact source point of view: no artefacts present (sitting scenario) and motion artefact present (walking scenario). The above proposed hierarchical approach is applied for this example. Thus, first the state is detected (no artefact *vs.* motion artefact), then for each state a separate classifier is created. In order to show the potential improvement with this approach, results are compared to a baseline without artefact detection.

For splitting the entire dataset into training and testing parts, 10-fold cross-validation is applied. The entire training part is used to create a classifier which distinguishes the two states. The two locomotion labels (sit or walk) of the dataset are used for this task. Furthermore, two additional classifiers are trained: Using data from the sitting and walking scenario of the training part, respectively. The 12 activity labels of the dataset are used for these two tasks. The resulting three classifiers are summarised in Figure 3. These classifiers are then applied in a hierarchical way on the testing part, as shown in Figure 4. This way different strategies (classifiers) are used, depending on the identified artefact source.

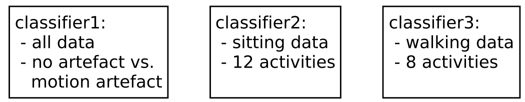

Figure 3: Classifiers created from the training part: used data and classification goal

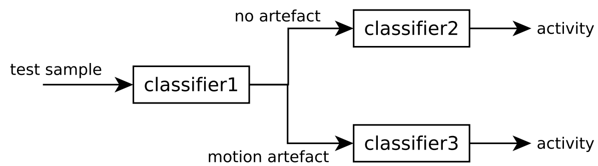

Figure 4: Classification of test samples: hierarchical artefact compensation

This paragraph describes the data processing steps applied on the capacitive sensor signals. A sliding window of $1.5\,$s length without overlap is used, as proposed in [1]. From each of the four channels, the following time-domain features are extracted: mean, standard deviation, minimum, maximum, dynamic range, and absolute integral. Moreover, for each pair of channels the signal correlation, difference of mean, and ratio of mean is computed. In total, 42 features are extracted on each signal window and used as input for the classification step. Three classification algorithms are compared: decision trees, AdaBoost.M1 and ConfAdaBoost.M1 (both boosting methods with decision trees as weak learners). The latter is a state-of-the-art, promising classifier for activity recognition problems [6]. Training of each of the classifiers is controlled to avoid class skew.

Results

Results comparing the proposed hierarchical artefact compensation to direct classification are presented in Table 1 (in form of class-normalised accuracy). It is clear that first detecting whether motion artefacts are present and then using a specific classifier is improving overall performance results: Error rate could be reduced by $20-30\%$ for each of the three classification algorithms. These results become more understandable when looking at the performance of individual classifiers of Figure 3. For example, when using the ConfAdaBoost.M1 algorithm, `classifier1` achieves an accuracy of over 0.99, while `classifier2` and `classifier3` achieve each around 0.90 accuracy. Classification problems become more complex when combining different states (sensor signals affected by different artefact sources), than when considering them as separate classification tasks. In case the different states can be distinguished in a reliable way (which is true in the here demonstrated example), it can be expected that a hierarchical approach outperforms the combined, direct classification approach.

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decision tree	0.67	0.58
AdaBoost.M1	0.84	0.78
ConfAdaBoost.M1	0.90	0.85

Table 1: Results (accuracy) comparing hierarchical artefact compensation and direct classification

Conclusion

This paper focused on how to decouple the application development for smart garments from the underlying sensing hardware. The previously introduced idea of a Garment OS was further elaborated by proposing a Garment OS architecture. This architecture defines the process of how application developers can access the available sensing capabilities. Moreover, the Garment OS architecture includes the main functionality required to hide the hardware-specific issues from the developer.

In order to realise the proposed Garment OS architecture, several challenges were identified. The task of a major component defined within the Garment OS is to extract the requested high-level information from sensor data. A challenge here is to compensate different artefacts, affecting sensor signals in garment-based systems. This paper proposed a hierarchical approach for artefact compensation. The approach was demonstrated on a concrete example of reducing motion artefacts in activity recognition, showing promising results. Benefits of the proposed hierarchical concept are that no additional sensors are required as artefact reference (opposed to adaptive filtering approaches), and that no expertise concerning the artefact source and how to specifically reduce it is required (opposed to most classical filtering approaches). A limitation of the proposed approach is given by the fact that for each identified state a separate classifier has to be trained. Therefore, it is planned in future work to investigate how the hierarchical artefact compensation concept can be scaled when multiple artefact sources are present.

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References

[1] Cheng, J., Amft, O., and Lukowicz, P. Active capacitive sensing: Exploring a new wearable sensing modality for activity recognition. In *Proceedings of 8th International Conference on Pervasive Computing (Pervasive)* (Helsinki, Finland, 2010), 319–336.

[2] Cheng, J., Lukowicz, P., Henze, N., Schmidt, A., Amft, O., Salvatore, G. A., and Tröster, G. Smart Textiles : From Niche to Mainstream. *IEEE Pervasive Computing 12*, 3 (2013), 81–84.

[3] Curone, D., Secco, E. L., Tognetti, A., Loriga, G., Dudnik, G., Risatti, M., Whyte, R., Bonfiglio, A., and Magenes, G. Smart garments for emergency operators: the ProeTEX project. *IEEE Transactions on Information Technology in Biomedicine 14*, 3 (2010), 694–701.

[4] De Luca, C. J., Gilmore, L. D., Kuznetsov, M., and Roy, S. H. Filtering the surface EMG signal: Movement artifact and baseline noise contamination. *Journal of Biomechanics 43*, 8 (2010), 1573–1579.

[5] Harms, H., Amft, O., Roggen, D., and Tröster, G. SMASH: A distributed sensing and processing garment for the classification of upper body postures. In *Proceedings of 3rd International Conference on Body Area Networks (BodyNets)* (2008).

[6] Reiss, A., Hendeby, G., and Stricker, D. Confidence-based Multiclass AdaBoost for Physical Activity Monitoring. In *Proceedings of 17th Annual International Symposium on Wearable Computers (ISWC)* (2013), 13–20.

[7] Sweeney, K. T., Ward, T. E., and McLoone, S. Artifact removal in physiological signals - practices and possibilities. *IEEE Transactions on Information Technology in Biomedicine 16*, 3 (2012), 488–500.

[8] Wood, L. B., and Asada, H. H. Active motion artifact reduction for wearable sensors using laguerre expansion and signal separation. In *Proceedings of 27th Annual International IEEE EMBS Conference*, vol. 4 (Shanghai, China, 2005), 3571–3574.

[9] Zhou, B., Cheng, J., Sundholm, M., and Lukowicz, P. From Smart Clothing to Smart Table Cloth: Design and Implementation of a Large Scale, Textile Pressure Matrix Sensor. In *Proceedings of 27th International Conference on Architecture of Computing Systems (ARCS)* (2014), 159–170.